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Research Article

The Global Transmission of Stock Market: A Spatial Analysis

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The stock markets, exhibiting complex self-correlation or cross-correlation over a broad range of time scales, are correlated not only in time but also in space. The conventional spatial weight matrix in the econometric analysis is short of economic relation between nonadjacent economic entities. Therefore, this paper applies the detrended cross-correlation analysis coefficient and partial correlation coefficient to analyze the global spatial interaction. This study computes the spatial Moran's I value by the two types of weight matrix for the 15 typical stock indices around the world, to explore the spatial agglomeration phenomenon. Then, the Spatial Durbin Model is applied to investigate the transmission of the stock market. The result from the Moran's I value indicates that the 15 typical stock indices are spatially correlated. The result of the Spatial Durbin Model gives the relationship among the closing price, the opening price, the highest price, and the lowest price.

1. Introduction

In recent years, there has been an increase in the concern about questions related to methodology in Spatial Econometrics, originated from the research of Paelinck, Klaassen [1], and Anselin [2]. The works of Anselin and Elhorst have played a fundamental role in modelling the spatial econometric models theoretically [2–5]. The spatial model mainly includes the spatial lag model (SLM), spatial error model (SEM), and Spatial Durbin Model (SDM) [6, 7]. LeSage and Pace proved that the spatial lag and spatial error model are special cases of the Spatial Durbin Model [8]. Consequently, the paper mainly uses the Spatial Durbin Model for research and prediction.

The theory of spatial weight matrix has been a key element of spatial analysis [9, 10]. A number of measurements of spatial weight matrix were proposed so that we can investigate the spatial process of geographical evolution from differing points of view. Today, the methods of SDM and spatial weight matrix have been applied to many fields. Jeetoo applied the SDM to investigate the determinants of renewable energy consumption using a balanced panel of 41 sub-Saharan Africa countries [11]. In this model, each element in the spatial weight matrix was equal to $1/d_{ij}$, where d_{ij} represents the distance between country i and country j. Zhang, Ma, Yang, and Wang used the SDM to investigate the impact of HSR on consumption from a spatial perspective, where each element in the spatial weight matrix was defined as $1/(\text{GDP}_i - \text{GDP}_j)$[12]. Hong, Liu, and Song applied the spatial panel model to analyze the spatial effect of the new economic momentum of China's high-quality development, where the spatial weight matrix is also calculated using the "economic distance" of the GDP of each province and city [13]. Wang, Zhang, Vilela, Liu, and Stanley constructed a spatial econometric model to explore the relationship between the capital market and industrial structure upgrading in China, where the spatial weight matrix is set based on the equal weight of geographical adjacency [14]. Cheung, Wong, Zhang, and Wu proposed a spatial panel model to explain the airport capacities as a combination of geo-economic and service-related factors, temporal correlation effects, and spatial spillover effects, where each element of spatial weight matrix is inverse square travel time between airport i and airport j [15].

The spatial correlation between stock markets may be influenced by other factors besides the spatial factor. Hence, we have to be alert to the possibilities of spurious correlation while investigating the spatial correlation. In order to remove the spurious correlation and improve the estimation performance for quantifying the intrinsic spatial correlation between stock markets, this paper proposes methods of the detrended cross-correlation analysis (DCCA) coefficient and partial correlation coefficient to construct the spatial weight matrix.

Podobnik and Stanley proposed the detrended cross-correlation analysis [16], and subsequently, the DCCA coefficient was introduced by Zenbende [17]. A remarkable characteristic of the DCCA coefficient is that it can investigate the cross-correlations between non-stationary time series at different time scales [18–20]. Owing to the cross-correlation between two variables may be affected by other variables; the partial correlation coefficient was proposed to measure the correlation between two random variables by eliminating the influence of a set of controlling random variables [21, 22].

The rest of the paper is organized as follows. Section 2 introduces the Moran Index, the DCCA coefficient method, and the partial correlation analysis. Section 3 shows the data and the spatial econometric model. Section 4 discusses the results obtained by the proposed methods. Finally, some conclusions are drawn in Section 5.

2. Method for Spatial Interaction of the Stock Market

2.1. Moran Index. Moran's index (Moran's I) method, as an analytical method, is used to reflect the degree of spatial connection on a spatial unit at a certain point in time. The Moran index is calculated as follows:

$$\text{Moran's}I = \frac{\sum_i^N \sum_j^N w_{ij}(y_i - \overline{y})(y_j - \overline{y})}{s^2 \sum_i^j \sum_i^j w_{ij}}, \quad (1)$$

where y_i represents the observations of different spatial units in the sample and w_{ij} is the element of spatial weight matrix. The mean and variance of the observations are $\overline{y} = 1/n\sum_{i=1}^N y_i$ and $s^2 = 1/n\sum_{i=1}^N (y_i - \overline{y})^2$, respectively. N denotes the total number of spatial units studied [23].

The value of the Moran index is generally between −1 and 1. If the index is larger than zero, there is a positive correlation in the research space; if the index is less than zero, there is a spatial negative correlation; if the Moran index is close to zero, it indicates that the variable has no spatial correlation.

2.2. Spatial Weight Matrix. We construct and employ three spatial weight matrices here. The first matrix (W^D) is based on the distance between the stock markets, the elements $W_{ij}^D = 1$ when stock market i and stock market j are adjacent; otherwise, $W_{ij}^D = 0$. The distance matrix relates the spatial location of the stock markets, reflecting the partial correlation between stock markets in the absence of economic relation between nonadjacent economic entity. Therefore, this paper proposes DCCA coefficients matrix to research essentially correlation between stock markets. Then, we analyze the correlation between two series by removing the effects of controlled variables, named detrended partial cross-correlation coefficient (DPCC) matrix. The flowchart of three spatial weight matrices is shown in Figure 1.

2.2.1. DCCA Coefficients Matrix. The DCCA coefficients weight matrix (W^{DCCA}) is constructed based on the DCCA coefficients between stock markets. For two simultaneous observations $x(i)$ and $y(i)$, the DCCA coefficient algorithm is as follows.

The first step is to construct the profiles $x_t = \sum_{k=1}^t x(k)$ and $y_t = \sum_{k=1}^t y(k)$ of two time series.

Then, two profiles are divided into $N_n = [N/n]$ non-overlapping boxes of equal length n $(10 \le n \le N/4)$, respectively.

For each box, local trends $\widetilde{x}_k$ and $\widetilde{y}_k$ are estimated on the basis of a least-squares fit. The corresponding detrended covariance is then calculated as

$$f_{\text{DCCA}}^2(n,k) = \frac{1}{n}\sum_{i=1}^n \left(x_{(k-1)n+i} - \widetilde{x}_{(k-1)n+i}\right)\left(y_{(k-1)n+i} - \widetilde{y}_{(k-1)n+i}\right). \quad (2)$$

The detrended covariance fluctuation function for scale n is given by

$$F_{\text{DCCA}}^2(n) = \frac{1}{N_n}\sum_{k=1}^{N_n} f_{\text{DCCA}}^2(n,k). \quad (3)$$

The DCCA coefficient is given as

$$\rho_{\text{DCCA}}(n) = \frac{F_{\text{DCCA}}^2(n)}{F_{\text{DFA}\{x\}}(n) F_{\text{DFA}\{y\}}(n)}, \quad (4)$$

where DFA refers to the Detrended Fluctuation Analysis [20, 24] and the range of DCCA coefficient is $-1 \le \rho_{\text{DCCA}}(n) \le 1$ [20, 25]. For measuring the correlated characteristic between two time series, we apply the mean of DCCA coefficients, $\rho_{\text{DCCA}} = \langle \rho_{\text{DCCA}}(n) \rangle$ in this paper.

The elements W_{ij}^{DCCA} of this matrix are calculated as follows:

$$w_{ij}^{\text{DCCA}} = \begin{cases} 1, & i \ne j, \rho_{ij} \ge \varphi, \\ 0, & i = j, \end{cases} \quad (5)$$

where ρ_{ij} is the DCCA coefficient of the units i and j in the sample. The threshold value φ is in the range of [0.7, 1].

2.2.2. Detrended Partial Correlation Coefficients Matrix. The third matrix W^{DPCC} is constructed based on the detrended partial cross-correlation coefficients (DPCC).

Partial correlation analyzes the correlation between $X_1' = X_1 - L_1(X_3, \ldots, X_p)$ and $X_2' = X_2 - L_2(X_3, \ldots, X_p)$, obtained by removing the effects of $X_3, X_4, \ldots, X_p$ from X_1, X_2, where the linear expressions are

$$\begin{aligned} L_1(X_3, \ldots, X_p) &= c_{01} + c_{31}X_3 + \cdots + c_{p1}X_p, \\ L_2(X_3, \ldots, X_p) &= c_{02} + c_{32}X_3 + \cdots + c_{p2}X_p. \end{aligned} \quad (6)$$

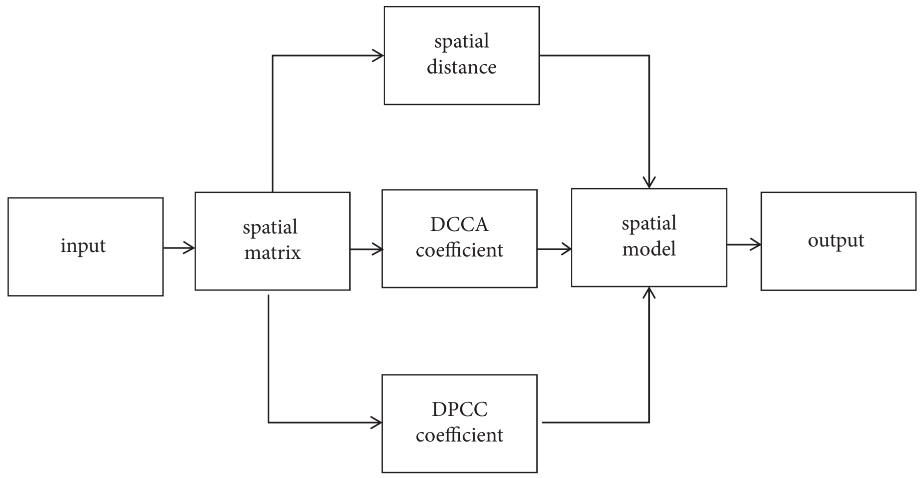

Figure 1: The flowchart of the method.

to minimize $E[X_1 - L_1(X_3, \ldots, X_p)]^2$ and $E[X_2 - L_2(X_3, \ldots, X_p)]^2$.

The partial correlation coefficient between X_i, X_j by eliminating the influence of the controlling variable, denoted by $\rho_{ij(1,2,\ldots,i-1,i+1,\ldots,j-1,j+1,\ldots,p)}$, is defined as follows:

$$\rho_{ij(1,2,\ldots,i-1,i+1,\ldots,j-1,j+1,\ldots,p)} = \frac{P_{ij}}{\sqrt{P_{ii}P_{jj}}},$$
$$P = \begin{pmatrix} \rho_{11} & \rho_{12} & \cdots & \rho_{1p} \\ \rho_{21} & \rho_{22} & \cdots & \rho_{2p} \\ \vdots & \vdots & \vdots & \vdots \\ \rho_{p1} & \rho_{p2} & \cdots & \rho_{pp} \end{pmatrix}, \tag{7}$$
$$= \begin{pmatrix} 1 & \rho_{12} & \cdots & \rho_{1p} \\ \rho_{21} & 1 & \cdots & \rho_{2p} \\ \vdots & \vdots & \vdots & \vdots \\ \rho_{p1} & \rho_{p2} & \cdots & 1 \end{pmatrix},$$

where matrix P is composed of $p \times p$ correlation coefficients ρ_{ij}, which is the DCCA correlation coefficient between X_i and X_j. P_{ij} is a subform of (i, j) element of matrix P. The mean of DCCA coefficients ise used to obtain the detrended partial cross-correlation coefficient (DPCC) here.

The elements W_{ij}^{DPCC} of the weight matrix are constructed as follows:

$$w_{ij}^{\mathrm{DPCC}} = \begin{cases} 1, & i \neq j, \rho_{ij(1,2,\ldots,i-1,i+1,\ldots,j-1,j+1,\ldots,p)} \geq \varphi, \\ 0, & i = j, \end{cases} \tag{8}$$

where $\rho_{ij(1,2,\ldots,i-1,i+1,\ldots,j-1,j+1,\ldots,p)}$ is the DPCC coefficient of the units i and j in the sample. The value φ is in the range of [0.7, 1].

3. Materials and Methods

3.1. Data. In this paper, we adopt the daily opening price, the highest price, the lowest price, and the closing price of fifteen stock indices, including the São Paulo Index (IBOV), the Dow Jones Index (DJI), the NASDAQ Index (NASDAQ), the Standard and Poor 500 Composite Stock Price Index (S&P 500), the FTSE Global Equity Index Series (FTSE), the French CAC 40 (CAC 40), the German DAX Index (DAX), the Nikkei 255 Index (N225), the Korea Composite Index (KS11), the Hang Seng Index (HSI), the Australian Standard & Poor's 200 (AS51), the Mumbai Index (SENSEX), the Russian Index (RTS), the Shanghai Composite Index (SSEC), and the Shenzhen Composite Index (SZI) from January 04, 1993, to January 03, 2019, as financial time series. We select 23 trading days' data from January 04, 2018, to February 09, 2018 to make stock prediction using spatial econometric models.

3.2. Spatial Econometric Model. The Spatial Durbin Model (SDM) takes the form [26]

$$y_{it} = \delta \sum_{j=1}^{N} w_{ij} y_{jt} + \alpha_0 + \mathbf{x}_{it}\boldsymbol{\beta} + \left(\sum_{j=1}^{N} w_{ij}\mathbf{x}_{jt} \right)\boldsymbol{\theta} + \varepsilon_{it}, \tag{9}$$

where y_{it} is the dependent variable of every unit in the sample $(i = 1, \ldots, N)$ at time $t\,(t = 1, \ldots, T)$. The spatially lagged dependent variable reflecting the interdependence of the unit i and the dependent variables of the unit j is represented as $\sum_{j=1}^{N} w_{ij} y_{jt}$. w_{ij} is the element of a $N \times N$ spatial weight matrix W, which describes whether the unit pairs i and j are interdependent, and δ measures the influence of these spatially weighted dependent variables. Commonly, the diagonal elements w_{ii} are set to zero because the units cannot depend on each other. x_{it} is a explanatory variables, and $\sum_{j=1}^{N} w_{ij} y_{jt}$ is the spatially lagged explanatory variable that represents the interdependence of the unit i with the explanatory variables of the units j in the sample. β

and θ are the corresponding $K \times 1$ vectors of the parameters to be estimated. ε_{it} is the independent and identically distributed random error term for all i and t with zero mean and variance σ^2. Finally, μ_{it} is a random error term, and its distribution is constrained by the spatial dependence of the Spatial Durbin Model.

4. Results

4.1. Result of Moran Index. In this section, the spatial distance matrix is applied to measure the Moran index for the 15 stock indices, as shown in Figure 2. It can be found that the Moran indices based on the spatial distance matrix are close to zero, which indicates the spatial independence of stock markets. However, this result is questionable in the absence of economic relation between nonadjacent economic entities.

In order to reveal the spatial correlation of stock markets, we propose the DCCA coefficient matrix, obtained by equation (5) with $\phi = 0.75$, to compute the Moran index. For comparison, the Moran index results based on the DCCA coefficient matrix are also shown with the spatial distance matrix results together in Figure 2. It is clearly shown that for stock markets, the Moran indices of DCCA coefficient matrix method are larger than those of the spatial distance matrix method, suggesting the existence of the spatial correlation in stock markets.

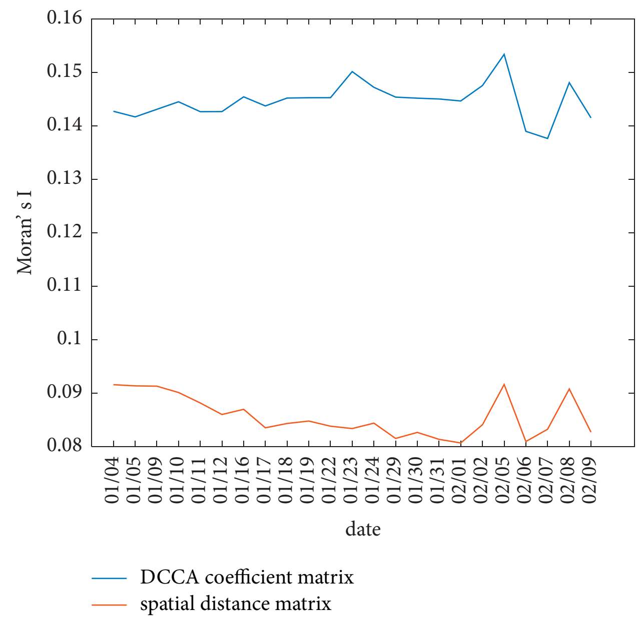

Figure 2: Moran's index based on the DCCA coefficient matrix (blue) and spatial distance matrix (red) for closing price of fifteen stock markets.

4.2. Result of Spatial Econometric Model. This paper determines that the dependent variable is the closing price of the stock. For applying the spatial econometric model, we calculated the DCCA coefficient between the closing price of the stock and each influencing factor. The results of the DCCA coefficient between the closing price and the opening price, the highest price, and the lowest price are 0.9971, 0.9982, and 0.9992, respectively. Consequently, we select explanatory variables include the opening price, the highest price, and the lowest price.

To further exemplify the potential utility of spatial econometric model for predicting the stock closing prices, we compare the prediction relative errors obtained by the spatial econometric model and the nearest neighbor algorithm (NN), where the relative error is as follows:

$$\left|\frac{y_{\text{prediction}} - y_{\text{truevalue}}}{y_{\text{truevalue}}}\right|. \tag{10}$$

This is due to the fact that the nearest neighbor algorithm (NN) is one of the most essential and effective algorithms for data segregation [27]. Figure 3 displays the relative errors of the stock closing price of SZI. The smallest value is 0.000479 and the largest value is 0.01394, obtained by SDM. For comparison, the smallest value (0.001383) and the largest value (0.036309), acquired by NN, are shown in Figure 3. It is obvious that the relative error obtained by using SDM is smaller, indicating that a spatial econometric model can better predict the closing price of stocks.

Figure 4 displays the relative errors between the predicted results and the real data of the stock closing price, the stock markets including GDAXI, SPX, IXIC, and DJI. We can clearly find that the prediction results obtained by using the Spatial Durbin Model are closer to the real data. The mean and variance of the relative error between the predicted result and the actual data of the stock closing price in fifteen stock markets are shown in Figure 5. The means, calculated by the Spatial Durbin Model, is smaller than the nearest neighbor algorithm. Therefore, compared with the nearest neighbor algorithm, the prediction of the spatial econometric model is more accurate. We notice that the variances of SDM are smaller than that of NN, implying the better robustness of SDM.

Next, the closing price of stocks is predicted by using the Spatial Durbin Model based on spatial weight matrix W_{ij}^{DPCC}, where the elements of the weight matrix is W_{ij}^{DPCC}

$$w_{ij}^{\text{DPCC}} = \begin{cases} 1, & i \neq j, \rho_{ij\cdot(1,2,\ldots,i-1,i+1,\ldots,j-1,j+1,\ldots,p)} \geq 0.75, \\ 0, & i = j. \end{cases} \tag{11}$$

Figure 6 shows the relative errors for the prediction of the stock closing price of SZI by using four different methods; the Spatial Durbin Model based on three spatial weight matrices (SDM (DCCA), SDM (DPCC), and SDM (Distance)) and the nearest neighbor algorithm (NN). It can be seen that the relative errors obtained by using SDM are small, and the effect of the spatial weight matrix constructed based on the DCCA coefficients and the DPCC coefficients is similar. Moreover, we calculate the relative errors for other stock markets such as GDAXI, SPX, IXIC, and DJI, as shown in Figure 7. It can be seen that these results are entirely consistent with the result in Figure 6. Therefore, the spatial econometric model based on the DCCA coefficient matrix and the DPCC coefficient matrix can better predict the closing price of stocks than NN.

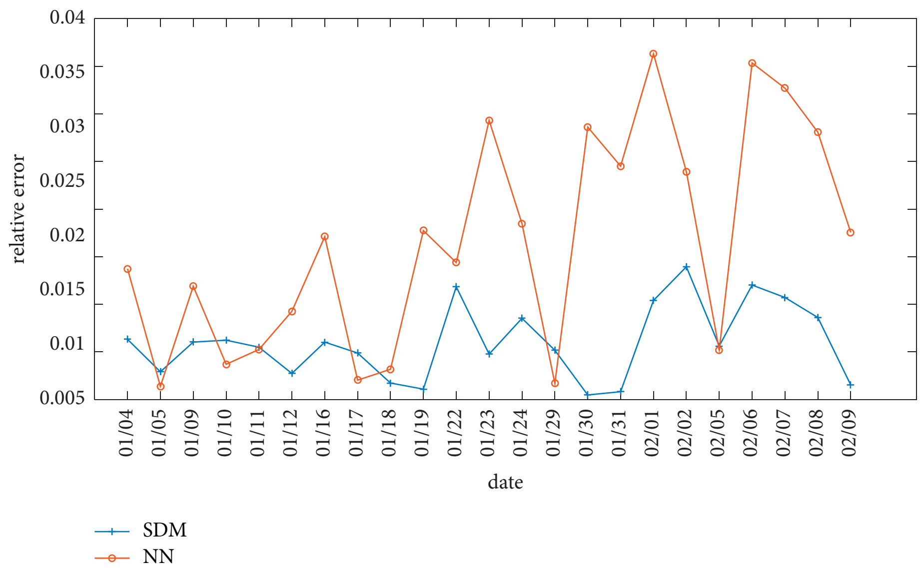

Figure 3: The relative errors of the stock closing price of SZI.

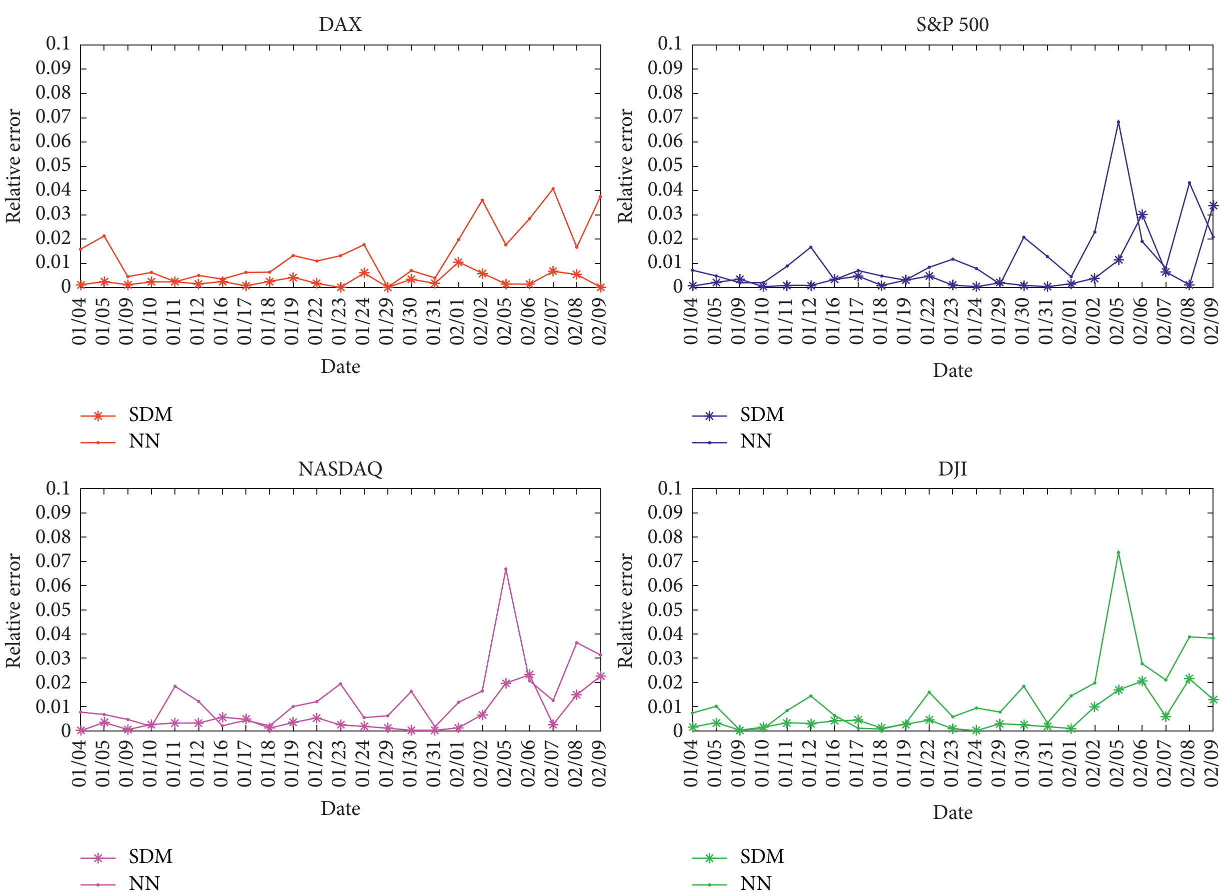

Figure 4: The relative errors of the stock closing price.

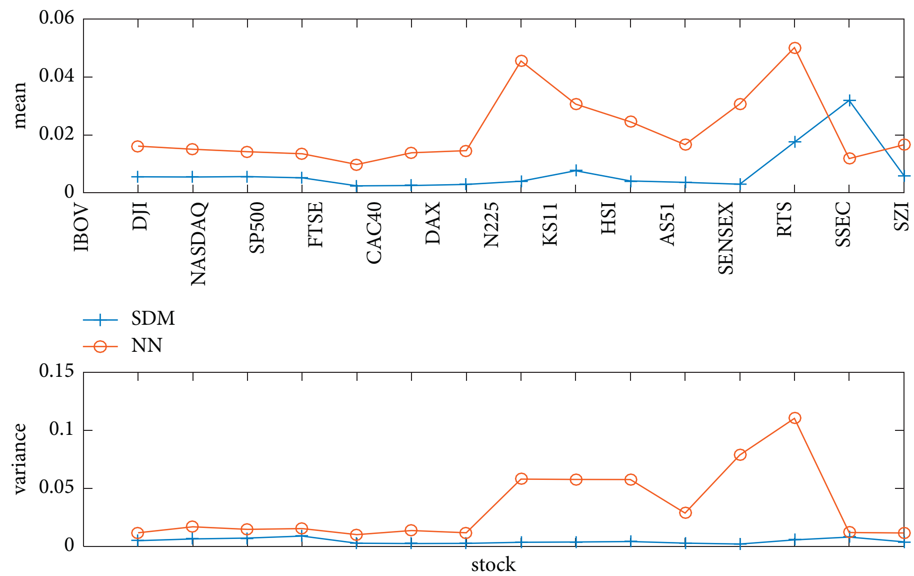

Figure 5: The mean and variance of relative errors.

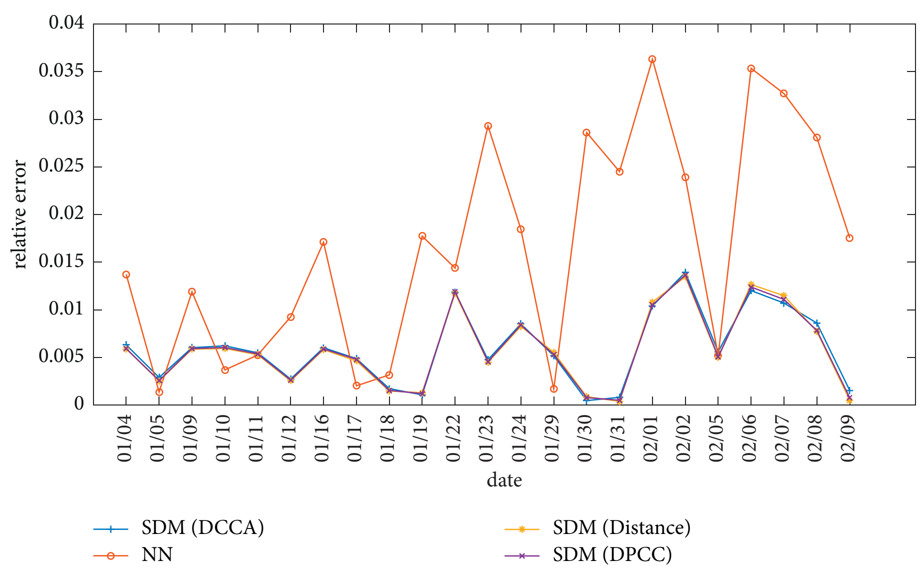

Figure 6: The relative errors obtained by using four different methods for the stock closing price of SZI.

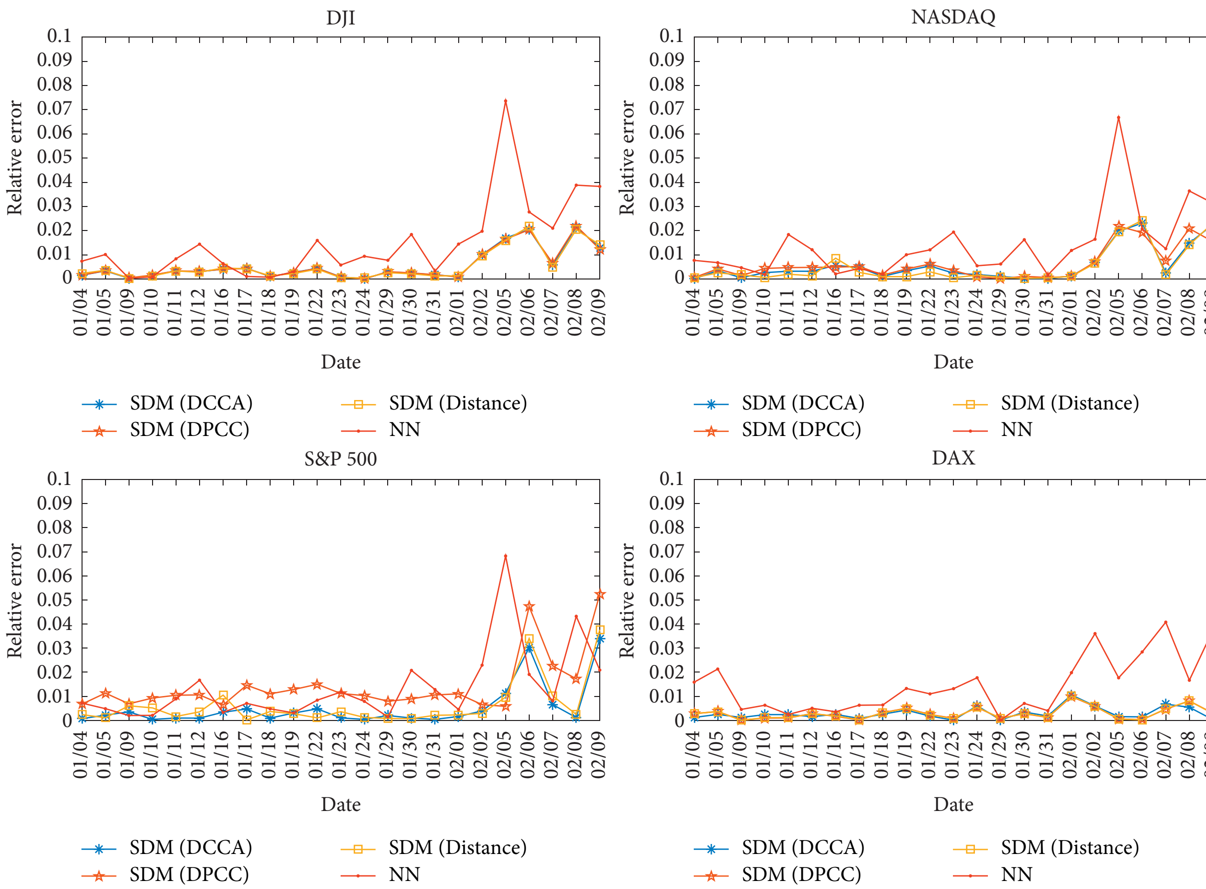

Figure 7: The relative errors obtained by using four different methods.

For Moran index test, our results indicate that concerning the stock index series, there exists a spatial correlation between the 15 typical stock indices. For a spatial model, our results give the relationship among the closing price, the opening price, the highest price, and the lowest price. In the following research, it is hoped that others can consider more variables on the basis of this research and choose a more suitable model for analysis.

5. Conclusion

DCCA is recently introduced to explore the correlation structure of the time series. In this paper, based on DCCA method, we use the Moran index to measure spatial interaction for stock index series. We carefully compare the spatial Moran's I value by the DCCA weight matrix with that of the spatial distance weight matrix. The result indicates that the DCCA weight matrix explores the economic relation between nonadjacent economic entities more efficiently.

In order to study the global spatial transmission of the stock market, the closing price, the opening price, the highest price, and the lowest price in fifteen stock markets are selected for analysis and modelling. The result of the Spatial Durbin Model gives the relationship among the closing price, the opening price, the highest price, and the lowest price. We compare the SDM with NN. The result indicates that the SDM is more accurate and robust.

For researching the spatial correlation between stock markets, the spatial weight matrix is required further investigation, both experimental and theoretical. While promising, the results of this paper should be considered as preliminary and their general applicability. Therefore, we do believe that our results may provide some help to research the spatial correlation between stock markets.

Data Availability

All data generated or analyzed during this study are included in this published article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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